A Human-Clothing Collision Detection Method Based on Ellipsoid Fitting (Postprint)

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Abstract

To achieve fast collision detection between garments and the human body in clothing simulation, a collision detection method based on ellipsoid fitting is proposed. First, using geodesic distance isolines as fundamental data, combined with the linear relationship between human body dimensions and height as well as human structural features, model feature points are extracted to achieve semantic segmentation of the model. Then, using the average radial distance as the fitting error between the ellipsoid and the model, a pruning-optimized bisecting K-means clustering algorithm is employed to progressively increase the number of cluster centers, enabling fast clustering of the human body model and generating a series of minimum-volume bounding ellipsoids that approximate the model. Finally, the generated bounding ellipsoids are used in place of the human body model for collision detection with the cloth. Experimental results demonstrate that the method not only enables rapid high-fidelity fitting to the three-dimensional human body model, but also effectively improves the computational efficiency of collision detection.

Full Text

A Cloth-Body Collision Detection Method Based on Ellipsoid Fitting

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Abstract: To achieve rapid collision detection between garments and human bodies in cloth simulation, this paper proposes a collision detection method based on ellipsoid fitting. First, geodesic distance isolines are used as fundamental data, and model feature points are extracted by combining the linear relationship between body dimensions and height with structural characteristics of the human body, enabling semantic segmentation of the model. Second, the average radial distance is employed as the fitting error between an ellipsoid and the model. The number of cluster centers is gradually increased using a pruning-optimized bisecting K-means clustering algorithm, enabling rapid clustering of the human model and generating a series of minimum-volume enclosing ellipsoids that approximate the model. Finally, the generated bounding ellipsoids replace the human model for collision detection with the cloth. Experimental results demonstrate that this method not only enables rapid, high-fidelity fitting of 3D human models but also effectively improves the computational efficiency of collision detection.

Keywords: collision detection; geodesic distance; model segmentation; minimum volume enclosing ellipsoid; bisecting K-means clustering

0 Introduction

In virtual garment simulation systems, collision detection is a critical factor determining visual realism and the most time-consuming component. Rapidly detecting collisions between garments and human models and generating appropriate responses is essential for real-time try-on experiences. Numerous researchers have conducted in-depth studies on this problem, achieving promising results [1-3].

Two classic algorithm families have emerged: hierarchical bounding volume methods [4-8] and spatial decomposition methods. The former is widely used for collision detection between spatial geometric models in complex environments. Salazar et al. [4] achieved dynamic real-time simulation of high-resolution cloth using axis-aligned bounding box (AABB) hierarchies and GPU multi-threading. Du et al. [5] also employed AABB bounding boxes to handle penetration between multi-layer garments, though penetration issues persist when garment granularity is too large. To address the poor tightness of AABB, Shen et al. [6] used oriented bounding boxes (OBB) and bounding spheres to construct a dual bounding volume hierarchy. This approach first culls non-intersecting objects via bounding spheres, then performs precise collision calculations using the tighter OBBs. While more efficient than pure OBB methods, this technique is unsuitable for collisions between objects in close proximity. Guo et al. [7] hybridized AABB and discrete orientation polytopes (k-DOP) to accelerate collision detection from organ deformation in virtual surgery, improving detection efficiency without sacrificing accuracy. Tang et al. [8] leveraged multi-core CPU parallelism combined with SIMD instructions to further optimize the k-DOP model, effectively enhancing collision detection efficiency for flexible fabrics on multi-core architectures, though the speedup from SIMD instructions decreases with a large number of cores. Zhang et al. [9] performed parallel collision detection using multi-core CPUs and GPUs, simplifying computational workloads. Du et al. [10] proposed a parallel continuous collision detection acceleration algorithm for distributed-memory GPU clusters. Ye et al. [11] employed a discrete intersection detection method to handle penetration between models, demonstrating better performance than traditional continuous collision detection for complex model surface deformations, though it cannot effectively handle intersecting surfaces.

For garment-body collision detection, garments fit tightly against the body with complex motion and easy deformation. Hierarchical bounding volume methods require real-time hierarchy updates during motion, making computational overhead a bottleneck. Given the orientation independence of spherical bounding volumes and the simplicity of collision response, Wang et al. [12] proposed a method for approximating solid models with spheres. Wang et al. [13] presented a 3D model sphere approximation approach based on voxelization, but the large number of internal spheres constructed makes it unsuitable for real-time collision detection. Li et al. [14] proposed a coherent collision detection method based on relationships between garment particles and connected triangle faces, achieving more than double the performance of traditional hierarchical bounding volume methods. Meanwhile, to address the lack of semantic information in human mesh models and the poor tightness of planar bounding volumes with complex hierarchies, Du et al. [15] performed Gaussian mixture model clustering segmentation using SDF. Wang et al. [16] proposed a triangular mesh segmentation algorithm based on concave-convex minimum boundary detection, which is robust but requires manual threshold adjustment for different scenarios. Liu et al. [17] used ellipsoids as primitives to construct hierarchical bounding volumes in a top-down manner, achieving effective approximation but at high computational cost. Meng et al. [18] initialized human model segmentation based on skeletal structure, then performed ellipsoid fitting and subdivision for each part, but this method depends on skeletal structure. Tang et al. [19] constructed adaptive ellipsoidal bounding boxes using an improved K-means clustering algorithm, then performed collision response in two categories based on surface error. This method is computationally expensive due to repeated backtracking.

This paper leverages the excellent surface fitting characteristics of ellipsoids for curved objects. Based on semantic model segmentation, we perform initial ellipsoid fitting. Different initial cluster centers and k-values are adopted for the torso and limbs, combined with a pruning-optimized bisecting K-means clustering algorithm for rapid ellipsoid fitting and cloth collision detection, yielding favorable simulation results.

1 Algorithm Framework

The algorithm consists of two stages: preprocessing and dynamic simulation. In the preprocessing stage, model feature points are extracted and geodesic distance algorithms enable semantic segmentation of complex models. The dynamic simulation stage comprises model fitting and collision response. First, minimum-volume enclosing ellipsoids perform initial fitting on segmented model data. Then, ellipsoids with large fitting errors are refined through subdivision.

Finally, optimized ellipsoids replace the original model for collision detection with cloth to produce final simulation results. The algorithm framework is shown in Figure 1 [Figure 1: see original paper].

2 Model Preprocessing

Since a single ellipsoid cannot effectively fit complex 3D models, the model must be simplified and segmented into sub-regions with relatively high fitting degrees to improve overall fitting quality. In human models, ellipsoids fit limbs well. Therefore, this paper achieves rapid and effective semantic segmentation based on human structural characteristics, using geodesic distance as fundamental data combined with the linear relationship between body part dimensions and height H.

2.1 Feature Point Extraction

This paper adopts the method proposed by Yu et al. [20] to automatically extract end feature points of the human model: the extremities of limbs and the top of the head (5 points total). Additionally, since human proportions remain relatively stable across heights, we analyze GB/T 10000-88 "Human Dimensions of Chinese Adults" [21] and GB/T 13547-92 "Workspace Human Dimensions" [22] to categorize human model feature points into three types: end feature points, middle-layer feature points, and inner-layer feature points. The linear relationships between body part dimensions and height H are calculated as shown in Table 1 . Based on this, combined with Dijkstra' s approximate geodesic distance algorithm, middle-layer feature points (elbow, knee, and neck points) are rapidly located.

Since the model used in this paper stands along the positive y-axis, height can be obtained by simply finding the maximum and minimum y-coordinate values: $H = y_{\max} - y_{\min}$. Then, using end feature points as reference points, the geodesic distance between any model point v_i and each end feature point p is calculated:

$$\mathrm{geod}(v_i, p), \quad (i = 0, 1, \dots, N - 1)$$

where v_i is the i-th vertex of the model, p is an end feature point, $\mathrm{geod}(v_i, p)$ is the geodesic distance between the two points, and N is the total number of vertices.

Given that human models consist of triangular meshes with varying densities, when a cross-section intersects the model, it must intersect with edges. To ensure computational accuracy, intersection points between the cross-section and triangular mesh must be solved by detecting all triangles in the model. As shown in Figure 2 [Figure 2: see original paper], the coordinates of point v_4 can be calculated using Equation (2). Similarly, point v_5 coordinates can be obtained.

The perineum point is defined as the point corresponding to half the geodesic distance between the two toe feature points. Leg length L_{leg} is the geodesic distance from the perineum point to the toe feature point: $L_{\text{leg}} = \text{geod}(v_5, p)$. To accurately segment the arms, combined with human model structural characteristics, the armpit point can be accurately extracted via point-to-line distance. As shown in Figure 3, v_3 is the point on the elbow' s geodesic isoline with minimum Euclidean distance to the perineum point; v_2 is the point on the isoline calculated with the right toe end feature point as reference that has maximum Euclidean distance from the perineum point. By sequentially comparing the projection distances d_i of all vertices v_i on the geodesic path between v_2 and v_3 to the line v_2v_3, the point with maximum projection distance is identified as the armpit point. The geodesic distance from this point to the corresponding fingertip feature point gives the arm length.

2.2 Model Segmentation

After obtaining human semantic feature points, hierarchical segmentation of the 3D human model can be completed via geodesic distance. For convenience, let the 3D model vertex set be $S = \{v_0, v_1, \dots, v_{N_S-1}\}$, where v_i is the i-th vertex and N_S is the total number of triangles. The ultimate goal of model segmentation is to partition all vertices according to structural characteristics. Taking arm segmentation as an example, for end feature point p and adjacent inner-layer feature point p', vertices belonging to the arm satisfy $\text{geod}(v_i, p) < \text{geod}(v_i, p')$. Similarly, under feature point constraints, leg and head segmentation results can be obtained. Remaining vertices constitute the torso, which is further divided into 6 parts based on waist height, chest height, and the perpendicular bisector planes of left/right armpit point connection lines. Finally, for segmented limbs, corresponding middle-layer feature points are identified to form a subset requiring secondary segmentation. Each part is further divided into two using Equation (3), completing semantic segmentation. As shown in Figure 4 [Figure 4: see original paper], both male and female model segmentation results effectively reflect human structural characteristics.

3 Ellipsoid Fitting

3.1 Minimum Volume Enclosing Ellipsoid

To address the low fitting degree of bounding boxes for curved surface models and the resulting high number of intersection tests in collision detection, this paper adopts ellipsoids as primitive bounding volumes for better curvature surface fitting. Using the method from literature [19], a 3D model point set S generates a series of minimum volume enclosing ellipsoids (MVEE) with the following properties:

A minimum volume enclosing ellipsoid is defined as:

$$\text{MVEE}(S) = \{x \in \mathbb{R}^3 : (x - c)^T Q (x - c) \leq 1\}$$

where Q is a 3×3 positive definite matrix and c is the center. The eigenvectors and eigenvalues of Q represent the semi-axis directions and lengths, respectively. The MVEE satisfies:

$$\mathrm{conv}(S) \subseteq \mathrm{MVEE}(S) \subseteq d \cdot \mathrm{conv}(S)$$

where $\mathrm{conv}(S)$ is the convex hull of S and d is a scaling factor.

After preprocessing, the human model is semantically divided into multiple regions $S = \{S_1, S_2, \dots, S_k\}$, ensuring segmentation consistency with human topology.

3.2 Ellipsoid Fitting Error

During ellipsoid fitting of sub-region S_j, the approximation error between the fitted ellipsoid and sub-region must be quantified. Simari et al. [23] used a weighted average of Euclidean radial distance, surface normal, and curvature as fitting criteria, achieving good results by controlling relative weights. Lu et al. [24] used volume error between the original model and ellipsoid for adaptive 3D model partitioning, but volume computation is complex and costly. Since this paper performs semantic segmentation first, ellipsoids already possess good fitting characteristics. Only local refinement is needed, without requiring precise error values. As shown in Equation (6), fitting error can be approximated by the average radial distance between sub-region surface points and the approximated surface:

$$E_j = \frac{1}{N_j} \sum_{i=1}^{N_j} \|v_i - v_i^{\varphi}\|$$

where E_j is the ellipsoid fitting error for model sub-region S_j, v_i is the i-th vertex on the sub-region surface, N_j is the total number of vertices in the sub-region, and v_i^{φ} represents the radial projection of vertex v_i onto the ellipsoid surface.

3.3 Ellipsoid Subdivision Optimization

After semantic segmentation and initial fitting, a series of ellipsoids matching surface features are obtained. However, large fitting errors remain in the torso region due to insufficient subdivision levels. While increasing global iteration count could reduce fitting error, it would cause over-segmentation, introduce numerous ellipsoids, fail to guarantee fitting accuracy, and significantly reduce collision detection efficiency. To achieve globally optimal torso fitting, this paper divides the torso into 6 parts based on waist height, chest height, and perpendicular bisector planes of left/right armpit point connection lines. The initial k-value for K-means clustering is set to 6, with mean coordinates of vertices in each of the 6 sub-regions serving as initial centroids. A pruning-optimized K-means clustering algorithm then performs secondary partitioning to obtain better-approximating ellipsoid structures.

The pruning optimization concept is as follows: In K-means convergence, no points transfer between clusters and centroids stop changing. The most significant convergence occurs in early algorithm stages. Therefore, to improve efficiency, the original termination condition can be modified to stop when the mean variation of k cluster centers falls below a specific threshold.

As shown in Figure 5 [Figure 5: see original paper], assuming initial $k = 3$, $p_{v,1}, p_{v,2}, p_{v,3}$ are mean coordinates of feature point domains in the sub-region, and $p'_{v,1}, p'_{v,2}, p'_{v,3}$ are corresponding next-step cluster centers. The clustering constraint is:

$$\|p_{v,i} - p'_{v,i}\| \leq \sigma, \quad i = 1, 2, 3$$

where $p_{v,i}, p'_{v,i}$ are centroid coordinates and σ is a preset threshold.

To ensure post-secondary partitioning quality and efficiency, this paper adopts Euclidean distance as the clustering criterion. While pruning, k-values and centers are incrementally added, and ellipsoid fitting error E_j is checked against preset threshold μ. Subdivision stops when the condition is met.

The algorithm steps are: a) Determine if the region is torso. If yes, initialize $k = 6$; otherwise $k = 1$. Perform pruning-optimized K-means clustering and compute MVEE for all clusters. b) Identify the ellipsoid with maximum fitting error. Split its point set using the two endpoints of its longest axis as new centers, discard the original center, and increment k by 1. c) Perform pruning-optimized K-means clustering on all points in the sub-region with the new k and centers. d) Recompute MVEE for the k new point sets. e) Compare all ellipsoid fitting errors E_j with threshold μ. If any $E_j > \mu$, return to step b); otherwise stop.

To ensure convergence of fitting error E_j, constraints are added during point reclassification:

$$E_i < E_j, \quad \forall i \neq j$$

where E_i, E_j are fitting errors of ellipsoids i and j. Ellipsoid i is the current ellipsoid containing the point, and ellipsoid j represents other bounding ellipsoids.

4 Collision Detection and Processing

As a highly deformable object with soft, flexible material properties that tightly covers the human surface, garment-cloth collision requires precise detection for realistic effects. Additionally, different garment types demand varying precision levels across body regions. To improve collision detection efficiency while ensuring computational speed and visual quality, this paper adopts dual fitting error standards with different thresholds μ for torso and limbs.

After completing ellipsoid fitting, these tightly-fitted ellipsoids replace the original model for collision detection. At regular intervals, collisions are detected.

Upon detection, corresponding particle velocities and positions are modified to prevent penetration. For a garment point p, Equation (9) computes ζ:

$$\zeta = (p - c)^T Q (p - c)$$

where Q is the ellipsoid' s positive definite matrix and c is its center. $\zeta > 1$ indicates no collision; $\zeta \leq 1$ indicates collision, with point p inside the ellipsoid. The point is moved to the nearest point on the ellipsoid surface along the line connecting the ellipsoid center and the vertex.

However, this method only works for a single ellipsoid. When handling multiple intersecting ellipsoids, vertices may be moved to incorrect positions. As shown in Figure 6a [Figure 6: see original paper], three error cases can occur when garment point p_0 collides with two intersecting ellipsoids:

Case 1: When vertex moves from p_0 to p_1, if p_0 is at an ellipsoid intersection, different response orders from each ellipsoid cause different results, leading to system instability.

Case 2: When vertex moves from p_0 to p_1, it is moved to ellipsoid O_0' s surface but remains inside ellipsoid O_1, so it is moved to O_1' s surface. However, since part of O_0 lies inside O_1, the point ultimately remains inside O_0.

Case 3: When vertex moves from p_0 to p_1, it is moved to the wrong side of the ellipsoid.

To address these issues, this paper divides collision processing into two stages: First, identify all ellipsoids colliding with the point and compute each collision intersection point. Then, calculate distances between these intersection points and the point's initial position. The ellipsoid with the minimum distance implies the earliest collision, so its intersection point is used as the response position.

As shown in Figure 6(b), if particle p_0 collides with ellipsoids O_0 and O_1 when moving to p_3, intersecting at P_0 and P_1 respectively, the minimum distance determines P_0 as the corrected position. The velocity is computed as:

$$v_c = v_n \cdot \frac{\|cP_0\|}{\|cP_0\| + \|P_0 p_0\|}$$

where v_c is the corrected velocity, v_n is the original velocity, and cP_0 is the vector from ellipsoid center c to P_0.

5 Experimental Results and Analysis

Experiments were conducted on a Windows 7 laptop with Intel(R) Core(TM) i3-2350M CPU @ 2.3GHz and 4GB RAM. Code was written in C++ using Visual Studio 2010, and all models were rendered with OpenGL. Human models were exported from Marvelous Designer 3 garment simulation software. The garment dynamics model followed literature [25], with dynamic simulation performed under gravity and wind forces [26].

This paper divides the human model into torso and limbs, using different initial K-values and fitting error thresholds. The mean coordinates of vertices in each torso sub-region serve as initial centroids. All segmented regions undergo pruning-optimized bisecting K-means clustering for ellipsoid subdivision. This approach effectively improves ellipsoid fitting error in the torso region while reducing K-means iterations, enhancing simulation speed.

For models in different poses with identical fitting error thresholds and clustering termination thresholds, controlling parameter values produces fitting effects shown in Figures 8(a)-(f). Figures 8(a)-(c) show Male Model 2; Figures 8(d)-(f) show Female Model 1. From left to right: single-ellipsoid initial fitting, same-threshold effect for torso and limbs, and different-threshold effect. Without considering fitting thresholds, initial torso fitting is poor. Subdivision-optimized ellipsoid fitting performs better, but using a uniform threshold yields many ellipsoids. Using different thresholds for different parts maintains fitting precision while reducing ellipsoid count, effectively improving collision detection efficiency.

To verify superiority in collision detection, our method was compared with literature [27] using the same Female Model 2. Vertex counts were increased for both human and garment models separately. Average per-frame collision detection times were compared, as shown in Figures 11 [Figure 11: see original paper] and 12 [Figure 12: see original paper] (units: seconds). Figure 11 shows that when only human model vertices increase, our method' s per-frame time remains nearly constant, while literature [27] shows linear growth. This is because our method only needs to determine garment vertex positions relative to fitted ellipsoids and update positions, eliminating dynamic bounding volume update time. Moreover, our method is insensitive to model vertex count—ellipsoid numbers change little with increasing vertices, so per-frame time doesn' t increase with vertex count. Literature [27] places non-adjacent triangle pair marking in the collision detection phase, reducing memory but increasing computational complexity. Figure 12 shows that when only garment model vertices increase, both methods' per-frame times grow steadily, but our method is 10× faster than literature [27]. Overall, our method' s average collision detection time outperforms literature [27].

Table 2 compares our method with literature [19]. For the same model with similar ellipsoid counts, our method is faster and provides better model approximation. Figures 9 [Figure 9: see original paper] and 10 [Figure 10: see original paper] show ellipsoids replacing character models for collision processing with garment meshes. Under gravity and wind, garments tightly attach to human models without penetration, yielding more realistic results than traditional bounding boxes.

Table 2: Comparison Between Our Method and Literature [19]

Model	Vertices	Ellipsoids	Literature [19]	Our Method (Segmentation+Fitting)
Male 1	4508	55	0.8 + 1.4	0.5 + 1.3
Female 1	8650	86	0.8 + 2.3	1.1 + 1.8
Male 2	8750	88	2.4 + 2.5	1.7 + 2.5
Female 2	8850	89	1.1 + 2.6	0.8 + 2.3

Times are in seconds (segmentation time + fitting time)

6 Conclusion

This paper proposes an ellipsoid-based collision detection method for garment simulation to address tightness and efficiency issues of human model bounding volumes. Compared with traditional bounding volumes, our method improves model segmentation speed through linear relationships between body part dimensions and height H without requiring precise segmentation. It generates a series of tight ellipsoids via pruning-optimized bisecting K-means iteration, improving fitting and collision detection efficiency. However, fitting error threshold μ must be set manually for different models. Currently, our method only handles static models. For dynamic models, ellipsoids could be bound to skeletons with dynamic updates only in joint regions—this represents future work.

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Note: Figure translations are in progress. See original paper for figures.